Efficient Frequency Domain Feature Extraction Model using EPS and LDA for Human Activity Recognition

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Abstract

Activity identification based on machine learning for human computing aims to understand or capture the state of human behavior, its environment, and integrate user by exploiting distinct types of sensors to give adjustment to the exogenous computing system. The ascent of universal computing systems requires our environment a solid requirement for novel methodologies of Human Computer Interaction (HCI). The recognition of human activities, commonly known as HAR can play a vital task in this regard. HAR has an appealing use in the health-care system and monitoring of Daily Living Activities (DLA) of elderly people by offering the input for the development of more interactive and cognitive environments. This paper is presenting a model for the recognition of Human Activities. In this proposed model, the Enveloped Power Spectrum (EPS) is used for extracting impulse components of the signal, and the Linear Discriminant Analysis (LDA) is used as a dimensionality reduction procedure to extract the discriminant features for human daily activity recognition. After completing EPS feature extraction techniques, LDA is performed on those extracted spectra for extracting features using the dimension reduction technique. Finally, the discriminant vocabulary vector is trained by the Multiclass Support Vector Machine (MCSVM) to classify human activities. For validating the proposed scheme, UCI-HAR datasets have been implemented which demonstrates higher recognition accuracy which has been acknowledged.

Keywords: Human Activity Recognition (HAR), Linear Discriminant Analysis (LDA), Enveloped Power Spectrum (EPS), Multiclass Support Vector Machine (MCSVM).

Introduction

Remote patient monitoring in these days is permitting the crippled and old patients a constant well-being and prosperity supervision while they perform standard exercises for a specific time-period every day. Ongoing populace benchmarks demonstrate that world populace is maturing quickly. For instance, the populace structure in Europe projected that the principle age bunches appear by 2060 the old (individuals more than 65 years) will be close 30% of its populace [1]. This speaks to a disturbing development of over 70% of this age gathering, conveying new difficulties to the examination network, which means to discover suitable choices for guaranteeing sound living to the general population. At present, the elderly people in the USA is nearly 46 million and it will increase to 98 million by the year 2060 which estimates that the older population will increase from 15% to 24% by this time. It is anticipated that this group of people will dramatically increase to the extent of approximately 98 million in amount by the end of 2060 giving rise to 23 percent of the entire population [2].

Human Daily Living Activity Recognition (HDLAR) is an examination field that means recognizing the activities completed by at least one subject. Accelerometer and other sensors can measure body movement and generate corresponding movement data. It can be connected to the acknowledgment of human exercises [3]. At the same time, the advancement of inertial sensors in smartphone devices, for example, accelerometers, gyroscopes, and magnetometers were initially created for improved UIs and gaming alternatives. But as on-time passes by, they have now used HAR researches on a large scale as Machine Learning technologies widely available for classification purposes. The researchers have implemented few methodologies in assorted application areas, for example, medicinal services, savvy homes, universal processing, encompassing helped living, observation, and security [4-7].

In modern days, smartphones are incorporated with versatile sensors by default and able to generate a discriminant dataset for different physical dispositions of humans. as different activities have different motions. The advancement of AR applications utilizing cell phones has a few focal points, for example, simple gadget compactness without the requirement for extra fixed hardware, what's more, solace to the client because of the inconspicuous detecting. This diverges from other set up AR approaches that use specific reason equipment gadgets, for example, in [8] or sensor body systems [9]. Although utilization of various sensors might have improved the execution of an acknowledgment calculation, it becomes improbable to anticipate the fact that people will utilize them in their day-to-day activities in the presence of difficulty and the extra time used in wearing them. One downside of this cellphone-based methodology is that vitality and administrations on the cell phone are imparted to different applications and this wind up necessary in gadgets with restricted assets. A novel feature extraction technique was proposed in [10] for HAR, where features were extracted using the Perceptual Linear Prediction (PLP) and Mel Frequency Cepstral Coefficients (MFCCs)., An unsupervised feature extraction model was proposed for human activity segmentation in [11]. Optimal feature extraction is a tough job in ML. Classification performance depends on extracted features. A useful feature extraction and selection model was proposed in [12], where for classification purpose SVM, an ensemble of classifiers, and subspace KNN were used. ML

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techniques that have been recently utilized for acknowledgment incorporate Gullible Bayes, SVMs, Threshold-based, and Markov chains [8]. Specifically, this research makes utilization of SVMs for classification as it was likewise utilized in [14]. In [19] presented the idea of an HF-SVM. The idea of this strategy is to use fixed point number-crunching in the SVM classifier. This feed-forward classifier permits the utilization of this calculation in equipment restricted gadgets. This research has used the same idea and expanded it for multiclass classification. On multichannel time series, human activities were recognized by the deep learning methodologies [21].

However, extracting informative features out of a myriad of digitized sensing signals seems to a tough task. In this regard, this research represents a feature extraction and dimension reduction model based on HAR. The EPS, followed by LDA are used for feature extraction based on dimensionality reduction of the signal spectrum. Finally, multiclass SVM is used with a view to recognize the Human Daily Living Activities (HDLA). In section 2, the proposed method of human daily living activity recognition has been described, followed by (i.e. section 3) performance evaluation of the implemented method with different experiments. Finally, Section 4 offers the concluding remarks.

Methodology

This research is targeted for the identification of the Human Daily Living Activity Recognition (HDLAR) grounded on accelerometer and gyro-meter signal. In Figure 1, depicts the working process in a block diagram. The details are described in three subsections correspondingly.

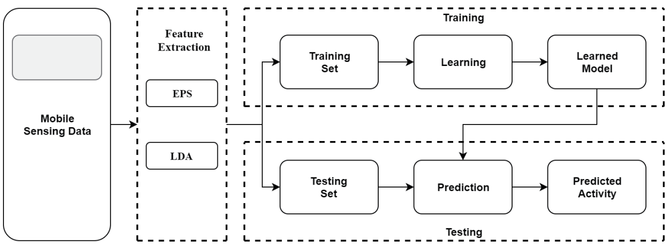

Fig. 1 Flow diagram of the proposed scheme.

A. Feature Extraction

Extract feature from signal is essential because of unwanted data into a signal. A plethora of feature extraction techniques is available for signal. In this study, the enveloped power spectrum (EPS) is used for extracting impulse from raw signal data. After performing EPS, Linear Discriminant Analysis (LDA) is performed on those obtained signal spectrums for vocabulary extraction and dimensionality reduction.

a. Enveloped Power Spectrum (EPS)

Imperative use of digital signal processing (DSP) is the enveloped power spectrum (EPS) for estimating the intermittent and irregular signals. The envelope spectrum allows reliable detection of regularities in the periodograms of the time series signal [22]. To investigate machinery signals like accelerometer, gyro-meter i.e., envelope analysis is one of the most powerful techniques for extracting the characteristic frequencies (or defect frequencies) of signal faults. Firstly, enveloped power spectrum's (EPS's) are calculated from original human activity signals using Fast Fourier Transform (FFT) where the periodogram function assesses the power spectrum. This function is characterized by N-point sequence y[n].

$$I_N(\omega) = \frac{1}{N}|Y(\omega)|^2$$

where,

$$Y(\omega) = \sum_{n=0}^{N-1} y[n]e^{-jwnT}$$

and Y(ω) is the discrete-time Fourier change of y[n].

$$R(n) = \frac{1}{N}\sum_{k=0}^{N-1} y[n+k]\bar{y}[k] \quad for \ |n| \le N-1$$

Or,

$$R(n) = 0 \quad elsewhere$$

It tends to be demonstrated that the converse change of the periodogram is the sample auto relationship function. The enveloped power spectrum of each activity signal is shown in Figure 2

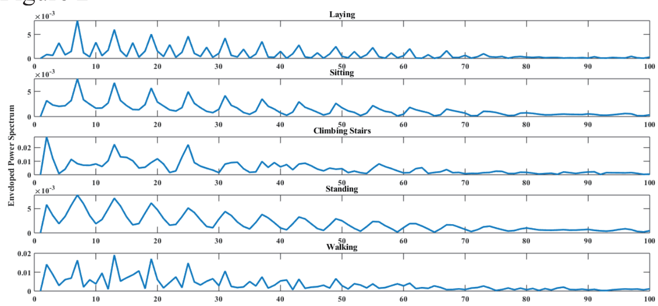

Fig. 2 Activity signal of the enveloped power spectrum.

b. Linear Discriminant Analysis (LDA)

In addition to feature extraction and reduction feature dimension, LDA searches the directions for maximum separation of classes. Separation between various data classes can be achieved by by Fisher's Linear Discriminant Analysis. It can preciously classify data.[23]. LDA can diminish the data dimension where the inside covariance class matrix was characterized by,

$$S_w = \sum_{k=1}^{k} S_k$$

where,

$$S_k = \sum_{n \in c_k} (x_n - m_k)(x_n - m_k)^T$$

and,

$$m_k = \frac{1}{N_k}\sum_{n \in c_k} x_n$$

and N_k is the amount of patterns in class c_k, k is the sum of classes, x_n is the discrete wavelet transform coefficient vector of n^{th} pattern and available in the data. The between-class covariance matrix is demarcated by,

$$S_B = \sum_{k=1}^{k} N_k(m_k - m)(m_k - m)^T$$

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where,

$$m = \frac{1}{N}\sum_{n=1}^{N} x_n = \frac{1}{N}\sum_{k=1}^{K} N_k m_k$$

is the global data mean. Similarly, the overall covariance matrix is demarcated by,

$$S_T = S_B + S_W$$

And the projection matrix is defined by,

$$W = argwmax\,\{(WS_W W^T)^{-1}\ (WS_B W^T)\}$$

The LDA coefficients were obtained from the projection matrix as,

$$y = W^T x$$

where x is the discrete wavelet transformcoefficient vector and y is the LDA coefficients vector .

B. Classification

At the final stage, human daily living activities are identified by using non linear Multi-class support vector machine (SVM). Though SVM is a binary classifier it can efficiently classify multi-classes by using a hyper-plane called margin. SVM is widely known for its classification performance which has the potential and capacity for pattern identification for high dimensional data. Although there are some data groups in versatile applications that do not allow to be separated in linear fashion. In other words, no suitable hyperplane exists that can separate the nonlinear datasets into two appropriate categories. In this situation Kernel function can be used to identify the inner meanings of these datasets. The polynomial functions, the hyperbolic tangent and the Gaussian radial basis function can be referred to as examples of nonlinear kernel functions. The technique that is used in this proposed model is the Gaussian radial basis function kernel. This kernel can classify the nonlinear datasets of attributes of activities. The function can be formulated in below:

$$w(ab_i, ab_j) = exp\left(\frac{\|ab_i, ab_j\|^2}{2\gamma^2}\right)$$

Capacity parameter w made from two distinct information namely ab_i, ab_j. The result the equation is computed with the help of free factor namely γ.

One of the SVMs is one-against-all (OAA) SVM. To classify the HAR, the experiment utilizes one-against-all (OAA) SVM.

Experiment

A. Dataset

In this study, UCI-HAR dataset is used [24]. UCI-HAR dataset contains in total 10299 numbers of signals with five humans daily living activities (Standing, Sitting, Laying, Walking, Climbing Stairs). Each signal contains 128 samples with three accelerometers (acc-x-total, acc-y-total, acc-z- total) and gyro-meter gyro-x, gyro-y, gyro-z) data. This UCI-HAR dataset is splitted into equal twofold subsets. One subset is used for training and and other subset is used for testing purposes. Figure 3 shows the sample activity signal.

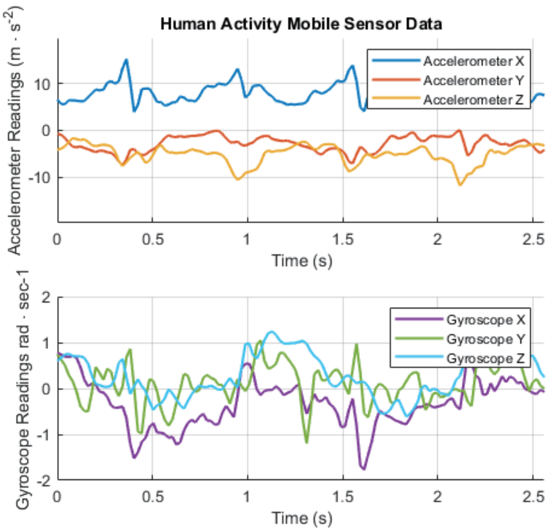

Fig. 3 Sample human activity signal.

B. Result Analysis

The described model uses the EPS for signal impulse extraction from sensing activity signal. After applying the EPS, 385 signal spectrums are obtained from 760 samples of a sample activity signal of UCI-HAR dataset. For feature extraction and dimensionality reduction, LDA is performed on extracted signal impulse. After completing feature extraction and dimensionality reduction technique LDA, the feature vector became 123 dimensions for each signal. Then a training feature vector is created for training purpose which is used to train the model. Lastly, the sensor extracted test feature vector is used for testing purposes. Table 1 shows the class-wise performance of each activity. As shown in Table 2, the model provides better performance from other recent technologies. The general accuracy of the given implementation is 98.67% for the UCI-HAR dataset.

TABLE 1
CLASS-WISE PERFORMACE (%) OF THE PROPOSED MODEL ON UCI-HAR DATASET.

Activity	**Method**		
	EPS+LDA+MCSVM		
	Sensitivity	Specificity	Accuracy
Standing	100	100	100
Sitting	100	100	100
Laying	100	100	100
Walking	92.69	93.97	93.33
ClimbingStairs	100	100	100

TABLE 2
PERFORMANCE (%) ASSESSMENT OF THE PROPOSED DESIGN WITH OTHER RECENT METHODS ON UCI-HAR DATA.

Authors	**Methods**	**Accuracy**
Yang et al. (2015)	CNN	85.10
Zhang et al. (2015)	DBN	83.30
Anguita et al. (2012)	Artificial features + SVM	89.00
Li et al. (2014)	Sparse autoencoder + SVM	92.16
Badem et al. (2016)	Stacked autoencoder	97.90
Ignatov et al. (2018)	CNN+Statistical features	97.63
Proposed Method	**EPS+LDA+MCSVM**	**98.67**

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Conclusion

In this paper, Human Activity Recognition (HAR) is conducted by a vocabulary extraction and reduction approach of dimensionality with the help of sensor generated signals. In this feature extraction and feature reduction approach, all features are extracted using EPS and LDA discriminant feature vector for classification purpose. Finally, Multiclass SVM classifier algorithm is utilized for classifying Human Activities. The extent of this research is to employ the present innovation for surrounding technologies, for example, in remote patient observing and smart environments. For validation purpose, experiments have conducted by UCI-HAR dataset. By applying the feature extraction based on EPS and LDA, the described method depicts better classification accuracy which has been acknowledged.

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